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Dipping in the policy mix: do R&D subsidies foster behavioral additionality effects of R&D tax credits?

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Dipping in the policy mix: do R&D subsidies foster behavioral additionality effects of R&D tax credits?[1]

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Abstract

We analyze behavioral additionality effects related to wage-based R&D tax credits and their dependence on the joint use of R&D subsidies. Using a matching approach combined with multivariate probit analyses on survey data of Belgian firms in 2006-2010, we find that tax credits cause firms not to 'do more of the same' (scale) nor 'do the same thing faster' (speed) but rather induce them to make more resolute changes to their R&D approach. In particular, firms are found to initiate additional R&D projects and tip the R&D-balance more towards research relative to development. The latter effect indicates that tax credits nudge firms' behavior towards those activities characterized by the most severe market failures. Furthermore, the behavioral additionality effects are found to increase with the relative importance of the tax credit for the firm. Finally, the effects of tax credits are positively moderated by R&D subsidies i.e. we find that a policy mix combining tax credits and subsidies is more effective than using tax credits only.

Keywords: Behavioral additionality – R&D tax credits – R&D subsidies – R&D policy mix.

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1. Introduction

Fiscal incentives have been used as enablers of R&D activity in a number of countries for a few decades now. The number of OECD members offering fiscal support for R&D more than doubled between 1995 and 2011 and equals three out of four. At the same time, the ratio of indirect versus direct support increased in close to half of the countries and is now at least of equal importance as R&D subsidies in over one third of the countries (OECD, 2013).

Consequently, the number of studies on the effects of indirect R&D support measures increased markedly in the past few years, as data became available. Additionality of R&D tax credits has been considered in recent studies in terms of effects on R&D inputs and outputs (Köhler *et al.*, 2012), but also on economic performance (Cappelen *et al.*, 2007; Czarnitzki *et al.*, 2011). However, in spite of a large and growing body of empirical work the effects of such fiscal policies are not yet fully understood (Köhler *et al.*, 2012; Lokshin & Mohnen, 2012; Zúñiga-Vicente *et al.*, 2014).

Our paper addresses behavioral additionality related to a volume based wage-related R&D tax credit and connects these differences to the policy mix of tax credits and R&D subsidies. Behavioral additionality refers to the difference a policy makes in the behavior of the supported firms (Buisseret *et al.*, 1995; Georghiou, 2002). The interest in behavioral additionality stems from the fact that the traditional input and output additionality concepts are thought to be limited in terms of capturing in a comprehensive manner the impact of public intervention on the innovation process itself (Georghiou, 2002; Falk, 2007).

So far, the behavioral additionality stream of literature has largely been ignored when it comes to additionality of R&D tax credits. This paper addresses this gap and, moreover, builds on prior work by taking into consideration the fact that firms often undergo multiple 'treatments', i.e. a combination of R&D tax credits and R&D subsidies. The additionality stemming from the blending of two or more public funding schemes has been addressed much less in previous research (see e.g. Falk *et al.*, 2009). By analyzing the combined effect of subsidies and tax credits, we fill a gap in the empirical literature on the synergies arising from the use of multiple R&D policy support measures. The potential for such synergies to occur – and the difficulty to assess them – stems from the inherent differences between direct and indirect support measures in terms of characteristics and goals. In particular, tax incentives tend not to interfere with general market mechanisms, have lower selectivity in terms of companies and industries, are easier to integrate in long-term financial planning and reduce the administrative burden compared to subsidies (Köhler *et al.*, 2012).

In line with the growing attention to R&D policy mixes – but so far only applied on input and output additionality (see e.g. Lhuillery et al., 2013; Busom *et al.*, 2012; Arqué and Mohnen, 2012), we explore different levels of 'mixtures' of tax credits and R&D subsidies by paying attention to the (relative) importance of the tax credit and of subsidies in the overall firm R&D activities.

The remainder of the paper is structured as follows. The next section reviews the literature on behavioral additionality and formulates hypotheses on the role of tax credits and the broader R&D policy mix. The third section provides background information on the availability and use of R&D subsidies and tax credits in Belgium and discusses the survey data and the empirical analysis. Section 4 presents the results and reports on various robustness checks. We conclude with a reflection on the main insights from our analysis for policy, and indicate avenues for further research.

2. Literature review

In this section, we give a more elaborate motivation for our focus on behavioral additionality and clarify how this paper builds on prior research. We first explain the concept of behavioral additionality and the way it can be measured. Next, we relate it to the importance of tax credits and to the R&D policy mix.

2.1. Behavioral additionality

The concept of behavioral additionality refers to permanent changes in firm processes and behavior as a result of policy intervention, such as newly acquired competences, the entry into new business areas or a change in working processes (Bach & Matt, 2002). Such changes occur due to learning effects and knowledge spillovers (Clarysse *et al.*, 2009).

The growing interest in behavioral additionality results from the fact that the traditional input and output additionality concepts can be questioned in terms of their ability to adequately capture the impact of public intervention on the innovation process itself (Falk, 2007). More specifically, it has been argued that government support can not only be motivated based on the neoclassical market failure argument, i.e. the aim to address underinvestment in knowledge production (Nelson, 1959; Arrow, 1962), but can alternatively be prompted from an evolutionary-systemic policy perspective (Flanagan *et al.*, 2011; Magro & Wilson, 2013). This perspective provides an alternative rationale for policy intervention in the sense that the primary purpose shifts to modify (in a permanent way) the firm's approach to R&D. This view naturally translates into behavioral additionality as a complementary way to evaluate policy support measures, besides the 'classical' input and output additionality approaches (Georghiou, 2002). Attention for behavioral additionality as an evaluation concept has further been justified by the argument that persistent changes in firm behavior create the necessary condition for a policy's ability to eventually induce output additionality (Davenport & Grimes, *cit. in* Georghiou, 2002, p59). Moreover, it is methodologically challenging to judge the effectiveness of public support in terms of output additionality, e.g. due to long lags before 'sleeper technologies' find a productive use (Luukkonen, 2000).

Behavioral additionality fits within an 'evolutionary-structuralist' perspective if the policy intervention ultimately leads not only to adjustments in the approach to R&D, but also to a change in cognitive capacity of the firm (Bach & Matt, 2002).

The OECD report on behavioral additionality (OECD, 2006) highlights that Finnish companies that had received R&D funding for specific projects mostly agreed that this permitted them to focus on long-term, but also riskier research. In Japan, national research funding allowed companies to engage in large-scale research projects and, to a greater extent, to improve the efficiency of R&D. Another series of case studies presented in the report investigate the impact of government support on R&D activities of firms, including accelerating projects or set-up of projects with higher technological challenges. These studies focused on behavioral additionality and made use of surveys and interviews. However, their results only refer to direct R&D public grants, rather than tax incentives – as is the case for our study – for which robust econometric estimations are scarce.

Falk (2007) integrates previous insights and addresses scope additionalities (expanded coverage of an activity to a wider range of markets, applications or players), advancement into new research areas (possibly reflected in a greater risk profile of the innovation projects), new partnerships between the business and academic spheres (resulting in cognitive capacity additionality – Bach and Matt, 2002), the timing of the project (acceleration additionalities which – if going hand in hand with scope additionality – can also result in long-term projects geared toward strategic objectives), and scale additionalities (engagement in larger innovation projects). Falk (2007) emphasizes that different aspects of behavioral additionality can and should be addressed in order to draw conclusions about the effectiveness of a policy measure. Georghiou (2002) refers to the UK Department of Trade and Industry that uses the subcategories scale, acceleration and scope additionality for measuring behavioral additionality.[2]

Different indicators have been proposed to empirically pin down the concept of behavioral additionality. In our data, we observe the following dimensions of a firm's R&D activities: scale, speed of execution, the ratio of 'R' (research) versus 'D' (development)[3], and the number of distinct projects that the firm is running (details will be given in section 3 and their relation with tax credits will be made clear at the beginning of section 2.2). These R&D descriptors allow assessing key aspects of behavioral additionality as they have been put forward in the literature. While not all of the 4 outcome variables at our disposal map clearly onto one of these dimensions, we believe the set of outcomes available in the survey allows

[2] Note that even more dimensions of behavioral additionality have been proposed in the literature, such as the expansion of a firm's network ('network additionality', see for example Idea Consult & Clarysse, 2006). In our empirical analysis, we do not have measures for such outcomes, so we necessarily leave them out of scope.
[3] Zúñiga-Vicente *et al.* (2014), in their literature review, reveal that studies that consider the impact of public support on research and development separately provide inconclusive results.

for a meaningful analysis of firms' behavioral responses to (a combination of) of R&D subsidies and tax credits.

2.2. Behavioral additionality effects as a function of the importance of tax credits

A key feature of R&D tax credits that motivates our interest in assessing their behavioral additionality effects is that the financial resources that become available through the tax credit can be freely spent by the firm. In other words, it is a distinct possibility that tax credits are not spent on R&D (deadweight loss – see Lokshin and Mohnen, 2012). Alternatively, they may be channeled to R&D activities, but in ways that do not represent a fundamental departure of the firm's usual way of doing R&D. In particular, the firm may increase the staffing of current projects, which may affect the scale[4] and/or speed of execution, without really changing the firm's R&D agenda. Conversely, a firm may also opt to take on additional R&D projects, or change the balance between 'research' and 'development' in its R&D portfolio.

Behavioral additionality effects of R&D tax credits are not guaranteed and, if they occur, may manifest themselves in different ways. In line with prior work that has found evidence of behavioral additionality due to R&D subsidies (Falk, 2007; Georghiou, 2002, Clarysse *et al.*, 2009) we hypothesize a positive effect on the scale, speed, number of projects and ratio of R versus D thanks to the reduction of wages of highly qualified R&D personnel.

We do not explicitly disentangle our hypothesis conditional on the outcome variable: this exploratory approach seems justified since prior work provides few handles to argue differential effects. However, given that we observe multiple outcome variables, which are only partially correlated, we can infer the firm's use of the tax credit from (the absence of) differential changes in these outcomes. First, if a firm redirects the reduction in wage costs to non-R&D activities or if R&D employees bargain for higher wages compensating the wage subsidy, then the tax credit will not have an effect on any of the outcome variables. Estimates by Goolsbee (1998) for the US and Haegeland and Møen (2007) for Norway indicate an important impact on wages by the R&D tax credit. For the Netherlands, Lokshin and Mohnen (2012) calculated that this effect reduces the effectiveness of Dutch tax incentives for R&D by 25 percent.

Conversely, if the firm does invest more in R&D then there will be a positive effect but which outcome variables are affected most depends on the precise response of the firm. First, if the firm decides to replace R&D workers who are not eligible for the measure by highly-qualified people who comply with the necessary formalities – and who therefore are likely to command

[4] Note that a firm may also respond by replacing employees who work on R&D projects but who are not eligible for the tax credit by people who do meet the formal requirements in terms of educational qualification. In that case, scale (in terms of people) would be unaffected by the tax credit.

higher wages – then this has an impact on the skill base of the company rather than the total R&D (wo)manpower. Hence, we may primarily expect an upward influence on the ratio of Research versus Development and/or the number of projects[5]. This without disregarding the differences and complementarities between research and development activities of companies in terms of aims, people, management style and outcomes (Barge-Gil & López, 2013). An alternative response could be that the firm does not engage in increasing the share of highly qualified R&D workers but instead chooses to hire more people to help executing R&D work, e.g. lab technicians, who do not represent a substantial expansion of the firm's expertise. In that case, one would first and foremost expect an effect on the scale and speed of R&D activities, rather than the other, more scope-oriented outcomes. The distinction between basic and applied research and more commercially oriented development interferes with our measure capturing more research-oriented behavior (OECD, 2002). While the actual reaction of a given firm will end up somewhere along the spectrum of skill-upgrading versus pure capacity-building, these alternatives provide a useful framework for making sense of differential effects across the sub-dimensions of behavioral additionality.

In addition, we hypothesize a volume-induced behavioral additionality effect of the tax credit: firms with a higher share of employees benefiting from R&D tax credits are expected to exhibit stronger BA effects. The intuition is that specialized human capital is the key input into the R&D process, so if a larger share of the firm's staff benefits from this measure, we expect a stronger effect.

Hypothesis 1: the behavioral additionality effects of R&D tax credits increase with the importance of these tax credits for the firm.

2.3. Behavioral additionality of R&D tax credits in the presence of R&D subsidies

There is a long-standing interest in the interactions that may arise in a 'mix' of policy instruments: Cunningham *et al.* (2013) trace the emergence of the policy mix concept in the policy-oriented literature back to the 1990s. Supported by the growing emphasis on a systemic view of innovation scholars and policy makers have banked on the concept to better understand the complexities in stimulating innovation. (Nauwelaers *et al.*, 2009; OECD, 2010). Despite the need of a more comprehensive approach for evaluating the interactions between different support measures (Diez, 2002; Aranguren *et al.*, 2013), the policy mix concept remains a rather ill defined and under-conceptualized term (Flanagan *et al.*, 2011). In this paper, we operationalize the policy mix as the joint use of R&D tax incentives and subsidies, which are by far the two most important policy instruments used to stimulate

[5] Under the assumption that a more diverse skill base represents an incentive to undertake more projects where those skills are put to use.

private R&D activity (OECD, 2010). We briefly introduce the key differences between these instruments in terms of their objectives and use by firms.

In general, subsidies provide up-front financing independent of the firm's tax position and are more interesting for firms facing appropriability difficulties. Subsidies may also help to attract additional funding since they provide a certification effect, unlike tax credits (Takalo & Tanayama, 2010). On the other hand, tax incentives typically require less administrative burden and do not suffer from winner-picking by government agencies, but require that the firm has the capacity to appropriate the returns of its innovation to benefit from the measure (Busom *et al.*, 2012). Related to the latter argument, tax incentives are more likely to benefit stable R&D performers, whereas subsidies tend to increase the number of R&D performers (Busom *et al.*, 2012; Arqué and Mohnen, 2012).

In terms of criteria, subsidies are typically awarded based on innovative content of the proposal, technical ability of the firm and potential market (Busom *et al.*, 2012; Takalo *et al.*, 2011). Conversely, R&D tax credits do not require the approval of a specific government agency and funding is provided irrespective of the quality of the project. An advantage of a tax-based subsidy is that it leaves the choice of how to conduct and pursue R&D programs in the hands of the private sector and thus avoids inefficiencies due to uninformed steering of firms' R&D (Hall & Van Reenen, 2000). At the same time, this allows firms to fund R&D projects that yield the highest private return rather than the ones with the highest social value (David *et al.*, 2000). Furthermore, the existence of tax deductibles may tempt firms to game the system, for example by labeling expenses as research activities while in fact they are related to other kinds of business activities only vaguely related to research (Antonelli and Crespi, 2011).[6] R&D subsidies that impose conditions on the execution of R&D may, in principle, improve allocation decisions, but issues like asymmetric information, lobbying and red tape may lead to suboptimal funding decisions (Hall and Van Reenen, 2000).

Given that the policy goals and granting mechanisms of tax credits and subsidies are quite different, it is not trivial to predict the results when they are used jointly. In fact, little is known about the interaction between R&D tax incentives and direct subsidies for R&D. More in general, which particular form public support should be used to correct for market failures is not clear, nor is the question whether or not there exists an optimal mix of tax credits and subsidies (Busom *et al.*, 2012).

Most existing input or output additionality studies that consider multiple instruments do not analyze interactions. Cunningham *et al.* (2012) report higher success levels of firms that combine direct and indirect support. Haegeland and Møen (2007) find that both subsidies and tax credits lead to input additionality but they don't explicitly study interactions. Carboni

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[6] As we will explain in section 3.1, this is not an issue for tax credits in Belgium since they effectively function as a wage credit rather than a deductible on firm profits.

(2011) studies Italian firms and finds evidence of input additionality with tax incentives appearing be more effective than direct grants, although grants encouraged the use of funding sources internal to the firm. Corchuelo and Martínez-Ros (2009) find evidence of a stepping stone logic, with Spanish firms that receive a subsidy being more likely to take advantage of the tax credit. Finally, Falk (2007) reports evidence that firms enjoying a mix of direct and indirect measures have a higher likelihood to innovate radically.

Bérubé & Mohnen (2009) apply matching estimators to show that Canadian firms using a mix of tax credits and subsidies have a higher innovative performance than firms using only tax credits. We will follow a similar set-up in this paper, albeit that we will zoom in on behavioral additionality rather than innovation outputs.

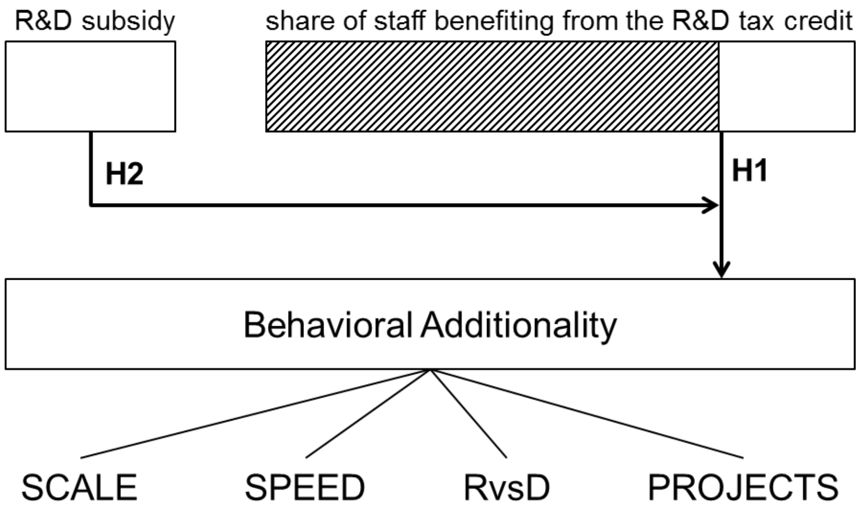
As a first contribution to the literature on the policy mix of R&D, we analyze whether subsidies moderate the behavioral additionality effects of tax credits. The intuition for such an interaction effect is the following. While R&D subsidies are targeted towards specific R&D projects, there may be 'spillovers' with respect to the way R&D tax credits are used by the firm. In order to justify the existence of such spillovers, one needs to answer the question what the subsidy (i.e. R&D project) accomplishes in terms of changing the R&D environment such that the firm uses the tax credit differently than firms who do not enjoy an R&D subsidy. We argue that it may be a very real possibility that subsidized firms direct the financial resources freed up by the tax incentive towards the subsidized project(s). In other words, those financial resources may find a 'productive home' within the context of the subsidized project.[7] More specifically, the subsidized R&D projects may serve as a roadmap, pointing out a more productive way for allocating additional R&D resources. For example, the tax credit may create room for additional experimentation that the firm otherwise would not have undertaken. In contrast, unsubsidized firms may be more conservative in spending the tax credit i.e. by doing more incremental R&D. This link between subsidies and tax credits ties into earlier work (Corchuelo & Martínez-Ros, 2009), which found that firms that use subsidies are more likely to employ tax credits as well. We expect that the internal awareness and R&D procedures that enable firms to tap into both measures extend to resource allocation decisions.

<u>Hypothesis 2</u>: *the behavioral additionality effects of R&D tax credits are stronger for firms that also receive an R&D subsidy versus firms that only benefit from tax credits.*

Figure 1 provides a schematic overview of the key variables and the formulated hypotheses.

[7] Note that our interest is in the behavioral additionality effects of the tax credit, but nothing excludes the firm's use of the tax credit for the subsidized projects.

Figure 1: Overview of hypotheses



3. Background, Data & Method

3.1. R&D subsidies and R&D tax credits in Belgium

Since our empirical analysis is based on Belgian data, in this section we highlight the main features of the R&D tax credit and subsidy system. A first important remark is that fiscal policy – and thus R&D tax credits – are a federal authority while R&D subsidies are predominantly[8] awarded by the three regions, i.e. Flanders, Wallonia and the Brussels Capital Region.

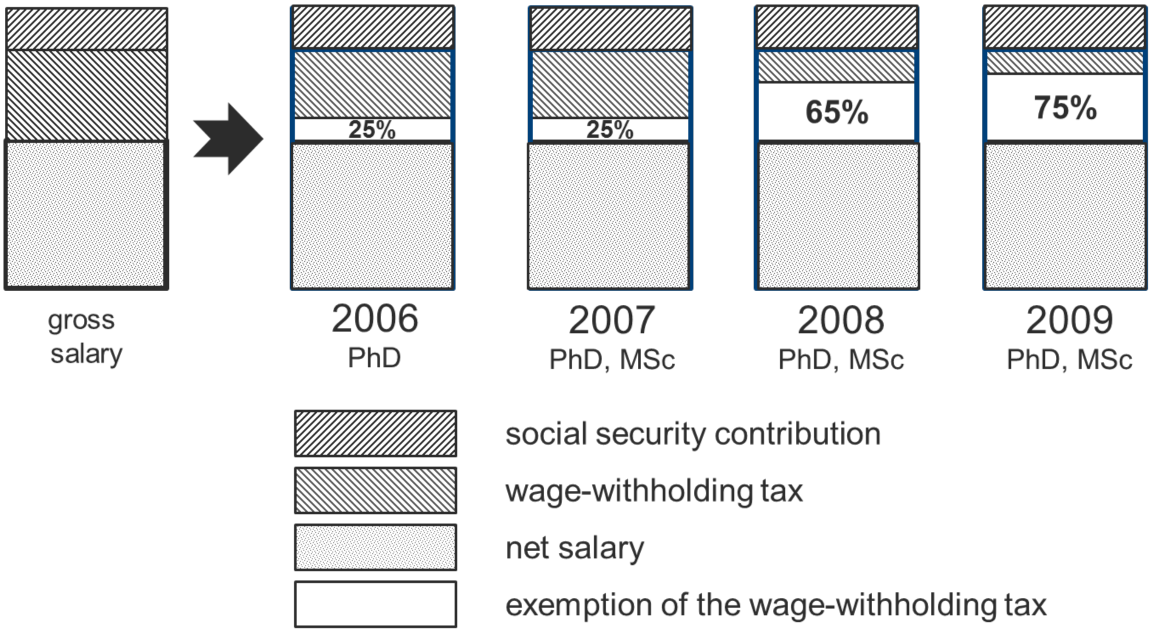
As in many other countries (Busom *et al.*, 2012; OECD, 2013), R&D subsidies have long been the most important source of direct funding for R&D in Belgium. Subsidy policies are largely inspired by a bottom-up approach, meaning that they are tailored to the specificities of the enterprises located in the region. Important aims of the programs include fostering co-operative research and innovation networking, in order to stimulate the use of scientific knowledge. R&D subsidies tend to be not primarily aimed at broadening the R&D portfolio of firms but rather seek to lower the threshold towards innovative projects with higher risk factors and some of the funding programs are exclusively oriented towards small and medium sized enterprises (Teirlinck & Spithoven, 2012).

Only more recently – since 2006 – R&D tax credits have been introduced on a larger scale.

The focus in our paper is on the additionality effects related to the introduction of the R&D tax credit, or, more accurately, the possibility for private firms to be partially exempted of the ‘wage-withholding tax’ for highly qualified R&D personnel. The operation of the measure is illustrated in Figure 2.

[8] About three fourths of the budget for R&D subsidies comes from the regions.

Figure 2: Operation of the R&D tax credit as a wage subsidy



The tax credit was introduced in January 2006 for researchers holding a PhD in exact or applied sciences, (veterinarian) medicines, or civil engineering. At the beginning of 2007 it was extended to researchers with a master's degree, with the exception of masters in the social sciences and humanities. The rate of exemption amounted to 25% and was increased to 65% in July 2008, to 75% in January 2009, and (out of scope for our analysis) augmented to 80% from June 2013 onwards.

There is high persistence in tax credit usage, with a very limited number of companies[9] abandoning the system once they started using it.[10] This implies that, the effects reported by beneficiary companies in the survey conducted in 2011 (discussed in the following section) tend to include the effects of the measure at its highest level of benefit to the companies and we can disregard the fact that the level of the tax benefit steadily increased over time.

As stated in the previous section, the exempted tax amount can be freely used by the company. While a strict condition to channel this reduction in wage cost back to R&D is absent, the aim of the policy measure is to stimulate R&D, and more particularly the employment of highly qualified researchers, as referred to in the earlier discussion of hypothesis 1. In this sense the tax credit measure is different from many other countries (see e.g. Busom *et al.*, 2012) in which it is depending on profit making by the company and it is a delayed and less certain R&D cost reduction (or revenue).

[9] Only 101 companies out of the cumulative population of tax credit users in between 2006 and 2009 have abandoned their use of the measure.
[10] Note that since the 'tax credit' effectively operates as a wage subsidy, a firm need not report a profit to benefit from the measure.

Both R&D tax credits by the federal government and R&D subsidies by regional governments represent sizeable public support for innovation in the business sector (8.4% of total Business Expenditures on R&D in the year 2009). By 2009, 1,086 companies benefitted from the tax credit, representing a reduction in wage cost of 225 million Euros. For R&D subsidies by regional governments, 160 million Euros were spent towards the private enterprise sector for 558 companies. The median tax credit per beneficiary company is 49,000 Euro compared to 86,000 Euro in the case of subsidies (Dumont, 2012).

3.2. Data

In June 2011 the Belgian Science Policy Office conducted an electronic questionnaire aimed to assess the behavioral additionality effects of the R&D tax credit measure explained in the previous section. The poll was sent to all firms in Belgium that were also surveyed in the 2010 OECD business R&D survey, which is based on the exhaustive inventory of 2,706 (quasi-)permanent R&D-active firms in the country. The electronic questionnaire yielded 412 responses. After internal consistency checks and removal of incomplete answers, a total of 192 firms provided information about all variables necessary for the analysis conducted in this paper. Data from the survey was combined with firm characteristics drawn from the Amadeus Financials database.

To assess the representativeness of sample respondents for the population of 1,131 R&D tax credit users in 2009 – the most recent year we have data for – both groups have been compared with respect to a broad array of firm characteristics. These include the overall firm size, sector and region of activity, current ratio, R&D intensity (share of researchers in total employees) and firm age, as well as the percentage of firms that have used the tax credit from 2006 (tax leaders). Statistical tests of differences in the means for the sample (i.e. firms in the survey) versus the population of tax credit users indicate that – while the sample is relatively small – it allows for a valid analysis[11].

We define our analysis sample as the surveyed companies that have used the tax credit (N=192), and we distinguish among them those that also used R&D subsidies (N=117). Thus, the control group comprises companies that have accessed the tax credit but not subsidies (N=75), and the treatment group is defined as using both measures.

The following indicators of firms' behavior in terms of R&D are available in the survey: scale, speed of execution, the ratio of 'R' (research) versus 'D' (development), and the number of R&D projects. More specifically, firms were asked[12] to what extent – on a 5-point Likert scale - the R&D tax credit affected each of these four behavioral outcomes relative to the counterfactual situation of not using the tax credit. As a way to deal with issues like

[11] The only statistically significant difference concerns low-tech manufacturing firms, which are slightly overrepresented in the sample.

[12] Given the data source, we need to assume that self-reporting qualitatively reflects the underlying data. Prior work (e.g. Haegeland & Møen, 2007) has shown that this is a legitimate assumption.

anchoring bias of respondents and make the empirical analysis more robust, the Likert-scale responses have been recoded into dichotomous variables.[13] Our empirical approach then boils down to comparing the answers for the companies that were also granted an R&D subsidy with those of companies that only benefited from the tax credit.

3.3. Method

Our aim is to identify the additionality created by the policy mix of tax credits combined with subsidies. Similarly to Bérubé and Mohnen (2009), our sample includes only users of the tax credit, with the 'treated' firms those that also benefit from an R&D subsidy. The outcome variables measure the effect of the *tax credit,* so the treatment captures whether the behavioral additionality due to the tax credit is moderated by the receipt of an R&D subsidy, the latter measured using a dummy variable.

We use y_{im}^{T} to denote the behavioral outcome m of firm i if it receives both R&D subsidies and tax credits $(S = 1)$, and y_{im}^{C} for the same outcome of the same firm if it uses only tax credits $(S = 0)$. Note that only one outcome is observed for each firm. Ignoring this issue for the moment, the effect for a firm i enjoying the policy mix of using both tax credits and subsidies instead of only tax credits is given by $E\left[y_{im}^{T} - y_{im}^{C} | S = 1\right]$. Empirically, the treatment effect for outcome m is then calculated as

$$SATT_m = \frac{1}{N_T} \sum_{i|S=1} \left[y_{im}^{T} - y_{im}^{C}\right]$$

with $SATT$ denoting the Sample Average Treatment Effect on the Treated and N_T the number of treated firms. It is not possible to directly calculate the effect of using both measures since only one outcome is observed for each firm i.e. there is a missing data problem (Heckman et al., 1997). The idea behind a matching approach is to find a proxy for the missing outcome by finding another firm with similar characteristics $X_i^{matching}$ but that only uses tax credits. The matching on observable characteristics addresses the problem of potential non-random selection of firms into the treatment, provided that the conditional independence assumption (CIA) holds (Rubin, 1977). This means that the treatment and potential outcome are assumed independent for firms with the same set of exogenous characteristics:

$$y_{im}^{T}, y_{im}^{C} \perp S_i | X_i^{matching} = x$$

[13] In particular, 'high' and 'very high' levels of agreement are coded 1 while lower levels or absence of agreement on influence are coded 0.

In addition, we impose the so-called common support restriction, which means that for all treated firms a valid counterpart should be present in the control group, and, conversely, every tax credit user should represent a potential subsidy recipient.[14]

Under these assumptions, we can rewrite the SATT as the mean difference of the matched samples:

$$SATT_m = \frac{1}{N}\sum_{i=1}^{N}\left[\left(y_{im}^{T}|S = 1, X_i^{matching} = x\right) - \left(y_{im}^{C}|S = 0, X_i^{matching} = x\right)\right]$$

Note that due to the nature of the survey questions, the matching design effectively yields a difference-in-differences estimation of the treatment effect. In particular, companies were asked what the *additional* effect of the R&D tax credit was on the scale, speed, etc. of their R&D. Thus, the answers represent the difference between the pre-treatment period t_0 and the post-treatment period t_1, the latter being the moment when the survey was conducted, in 2011.

Different methods exist to matching the treated firms with their most similar counterparts in the control group. We use the propensity score, $P\left(S = 1|X_i^{matching}\right)$, introduced by Rosenbaum and Rubin (1983), which is estimated using a probit regression. Subsequently, each treated company is matched to one firm from the control group based on the propensity score.[15] Matching treated and control firms using merely the propensity score can be a too coarse approach in the sense that it may mean that although a treated firm gets matched to a control firm with a similar score, they may still differ substantially in one or more of the key matching variables. Hybrid matching (Lechner, 1998) tries to trade off the benefits of the dimensionality reduction through propensity score matching on the one hand and the more accurate matching on individual covariates on the other hand, by combining the propensity scores with one or more 'key' matching variables. However, a condition for increasing the quality of matching this way is a sufficiently large control group so adequate matching partners can be found. Given the relatively small size of our sample, we therefore opted for a different approach that matches only on the propensity score.[16] Following the matching, we run follow-up regressions including – besides the treatment variable – the earlier matching variables to correct for any remaining imbalance in the covariates (Iacus *et al.,* 2011). Furthermore, we exploit the fact that we observe multiple behavioral outcomes in these

[14] In practice, this comes down to discarding all treated firms with propensity scores larger than the maximum and smaller than the minimum in the control group.

[15] We employ single nearest neighbor matching with replacement i.e. control firms are not removed from the pool of potential controls after matching with a treated firm. We follow this approach to ensure good quality matches given the specific composition of our sample: the treatment group is larger than the number of possible controls because most companies that have accessed tax credits also have used subsidies.

[16] As further support for matching on propensity score only, Abadie and Imbens (2006) show that using more than one continuous covariate for matching may result in a matching discrepancy of stochastic order $N^{1/K}$ with K the number of continuous matching variables and N the number of observations to match. If $K = 1$, the matching estimator is $\sqrt{N}$-consistent.

adjustment regressions by estimating a multivariate probit model, which allows for correlation between unobserved factors driving the behavioral outcomes of a single firm (while still requiring the error terms to be uncorrelated across firms) and hence a more efficient estimation. An additional benefit of the post-matching regressions is that they allow analyzing whether behavioral additionality depends on the importance of tax credits for the firm and/or the ratio of subsidies versus tax credits. We reckon this approach represents a reasonable trade-off between achieving a good-quality matching and accommodating the benefits and drawbacks of the available data.

We estimate the following 4-equation multivariate probit model of the behavioral additionality effects of tax credits:

$$y_{im}^* = \alpha_m + \beta^{matching\prime} X_i^{matching} + \beta^{subs\prime} X_i^{subs} + \beta^{tax\prime} X_i^{tax} + \varepsilon_{im} \; with \; m = 1..4$$

$$y_{im} = 1 \; if \; y_{im}^* > 0 \; and \; 0 \; otherwise$$

$X_i^{matching}$ denote the matching variables, which are included to control for remaining imbalance. X_i^{subs} denotes whether firm i received a subsidy, and X_i^{tax} measures the importance of the tax credit for firm i. The error terms ε_{im} are assumed multivariate normal[17] with mean 0 and variance-covariance matrix V where $\rho_{jj} = 1$ and the off-diagonal correlations are estimated from the data under the restriction that $\rho_{jk} = \rho_{kj}$.

Recall that the binary outcome variables y_{im} have been coded as 1 if the respondent at least agrees or strongly agrees there is an effect on the corresponding behavioral outcome, which is consistent with the idea of a latent variable y_{im}^* exceeding a threshold value.

4. Empirical Analysis

4.1. Matching

For the matching estimator, we include a range of variables that may be expected to affect the probability of a firm using both tax credits and subsidies as opposed to only tax credits. Note that since all firms in the sample make use of R&D tax credits, they may be expected to be relatively homogenous in the sense that all of them use public R&D support. While prior work provides little guidance on the precise characteristics that may distinguish, within the group of tax credit users, between subsidized and non-subsidized firms, we will draw on the matching literature to identify relevant matching variables.

Following Lhuillery *et al.* (2013) we first account for R&D intensity, measured as the percentage of researchers relative to the total number of employees. Note that many matching studies have analyzed input additionality and therefore used R&D investments as a dependent

[17] In our estimation of the model, we specified 30 random draws from the multivariate standard normal distribution to be used for calculating the simulated maximum likelihood function in each iteration. This exceeds the guideline of using at least $\sqrt{N}$ with N the number of observations (Cappellari & Jenkins, 2003).

variable rather than a covariate in the matching process. However, we study behavioral additionality i.e. how firms use their resources for R&D and therefore aim to make control firms comparable to treated firms in terms of the importance of R&D. If this variable were absent from the matching model, the possibility would remain that firms for which R&D is their 'core business' get matched to firms for which it is a less dominant activity. Furthermore, using R&D intensity as a matching variable is an additional way to control for industry (Mathieu & Van Pottelsberghe de la Potterie, 2010), besides the explicit industry classification we use, which is necessarily aggregate due to the relatively small size of the dataset. In particular, we use dummies for high- and low-tech manufacturing and service industries, following Eurostat guidelines.[18] Industry affiliation has also been shown to be a factor in the decision to grant subsidies to firms. Hyytinen and Toivanen (2005), for Finland, show that government funding disproportionately helps firms from industries that depend more on external financing. An important methodological concern about using R&D intensity as a matching variable is that it may be endogenous to the receipt of R&D subsidies as a grant may allow a firm to hire additional researchers. In other words, we need the pre-treatment R&D intensity, net of R&D employees financed through subsidies. Since we do not have information on the precise timing of subsidies – companies merely reported in the survey whether they benefited from an R&D subsidy or not – we use the following approach to mitigate endogeneity concerns. We rely on the observation that there is high persistence in who benefits from R&D subsidies (Busom *et al.*, 2012). Therefore, we corrected a (subsidized) firm's R&D intensity in the first year it is observed in the period of analysis (2006-2010) by using information in the survey on the relative importance for the firm of subsidies compared to tax credits, in the period 2006-2010. Jointly with the information on the amount of tax credit enjoyed by the firm, this allowed us to correct for the number of R&D workers supported by subsidies, and hence to calculate a 'subsidy-free' R&D intensity.

Company size has been found to have an impact on the use of public R&D support (Almus & Czarnitzki, 2003; Blanes & Busom, 2004; D. Czarnitzki & Licht, 2005; Aerts & Schmidt, 2008). We control for size by using the logarithm of the number of employees.

The experience of a firm in actively seeking and using other forms of R&D support may serve as a signal for its use of subsidies (Czarnitzki & Lopes-Bento, 2013; Lhuillery *et al.*, 2013). Hence we include a dummy (*taxleader*) capturing whether the firm used tax credits in 2006, the year the measure was introduced.

A firm's financial health is of importance when applying for subsidies because financially constrained firms need external financing sources more acutely (Caiumi, 2010; Kobayashi, 2011; Lhuillery et al., 2013), but at the same time they might not be primary targets for policy makers because of their uncertain financial future. We control for financial health by using the

[18] Also note that the use of a general industry classification is likely to be less relevant in our setting since only R&D-active companies are considered (Teirlinck et al., 2010).

current ratio, defined as current liabilities to current assets - a frequently used measure to capture the firm's financial position (Bromiley, 1991; Latham & Braun, 2010).

Finally, given that authority over R&D subsidy policy accrues to the regional governments, we include dummies for the three Belgian regions – Flanders, Wallonia and the Brussels Capital Region. As studies in other countries have also found (Santamaría *et al.*, 2010), the decentralization of policies leaves room for differentiation in terms of subsidy eligibility criteria, focus on specific industries, etc.

Means and proportions of the variables used for matching and the behavioral outcome variables are shown in the first and second panel of Table 1, respectively.

[Insert Table 1 here]

As expected from prior research (Bérubé & Mohnen, 2009), users of tax credits do not seem to differ very much from users of both tax credits and R&D subsidies. Indeed, in terms of R&D intensity, short-term financial health, industry membership and regional distribution, the two groups are rather balanced. However, significant differences in the averages of size and whether the firms used tax credits from their introduction point towards the necessity of balancing the two groups.

The second panel shows that there are significant differences in outcomes for the treated and potential control firms. On average, users of the policy mix reckon that the tax credit has increased the scale, speed, relative orientation towards research as well as the number of concurrent projects more than users of the tax credit only.

Table 2 shows the results of the probit estimation of the propensity to use both tax credits and R&D subsidies. As expected, companies that have used the tax credit since 2006 (tax leader) have a higher probability of also using subsidies. This confirms the intuition that these firms are more savvy at using different types of public support measures for R&D. Further, the matching results indicate that the control group (non-users of subsidies) contains on average more R&D-intensive and larger firms. This is in line with the target aim of subsidies towards commercialization and with particular attention to SMEs (Teirlinck & Spithoven, 2012). Bérubé and Mohnen (2009) find similar results for company size in their matching study, using an analogous treatment definition. Note however that these results should not be interpreted as general predictors of using R&D subsidies, but rather serve to identify differences in observable characteristics between treated and control firms.

Although the other variables such as industry affiliation and region have no significant effect on the probability to use R&D subsidies, they contribute to model fit and thus the overall balance between treated and control firms in the propensity score matching in the next step.

[Insert Table 2 here]

Since 10 treated companies are outside the common support region, the sample is reduced from 192 to 182 companies. The first panel of Table 3 confirms that none of the matching variables show significant differences in the means between the treated and control firms, indicating satisfactory balance. While the impact of the matching exercise on the sample is very modest, it has mainly served to assure that none of the subsequent results are driven by atypical firms.

[Insert Table 3 here]

Table 4 shows the average treatment effect on the treated (ATT) for each outcome. The share of firms reporting that the tax credit has allowed them to speed up R&D projects and/or increase the relative orientation of research versus development is substantially and significantly higher for recipients of R&D subsidies relative to those firms that only benefit from tax credits. Although the ATTs are also positive for the scale and number of R&D projects undertaken by firms, these effects are not significant. These results partially support our hypothesis on the positive interaction effect of R&D subsidies on the behavioral additionality of tax credits (H2).

[Insert table 4 here]

We now further ascertain the robustness of these results in a regression framework, which allows adding additional controls for imbalance between treated and control firms, and provide the more flexible specifications needed to test our hypotheses.

4.2. Regression analysis

Our first hypothesis states that the behavioral additionality effects of R&D tax credits increase with the importance of these tax credits for the firm. We test it by including the importance of the tax credit to the firm as a fractional variable[19]. The results[20] in Table 5 show that tax credits are not found to have an impact on the scale and speed of R&D. However, firms with a higher share of employees benefiting from R&D tax credits exhibit stronger additionality in terms of the number of R&D projects in their portfolio, and – although only marginally significant – a stronger research orientation versus development. The reason behind this effect could be that specialized human capital is a key input into R&D, and its lower cost induces significant changes in the way companies organize this process. In particular, the differential effects across outcomes lend themselves to the interpretation that firms, given an increasing reliance on R&D tax credits, invest more in highly-qualified human capital and that this allows them to fundamentally rearrange their approach to R&D rather than (merely) focus on

[19] The importance of the tax credit is measured as the share of R&D personnel (in headcounts) that benefitted from the tax credit in the most recent year.

[20] Note that we focus on the interpretation of the signs and statistical significance of the parameters, as evaluation of marginal effects is not trivial in multivariate probit models considering more than two outcomes (Cappellari & Jenkins, 2003; Mullahy, 2011). Moreover, the average treatment effects reported in the previous section indicated the increase in the share of companies showing the various types of behavioral additionality.

scale or efficiency.

[Insert Table 5 here]

The matching variables are included in the regressions to adjust for remaining imbalances in between treated and control firms and show significant results in a few cases, e.g. R&D intensity and industry. We also add indicators for the role of demand-pull and technology-push. More specifically, firms were asked in the survey whether these factors had an influence on the decision to perform additional R&D. The results show that only technology push has a significant, positive impact on the scale, speed and research orientation of projects. Finally, firms in the Brussels Capital Region are more likely to use tax credits to increase scale and speed of R&D than firms in Flanders and, to a lesser extent, Wallonia. A possible reason is the strong presence in Brussels of firms in IT (mainly software and consulting) for which R&D is arguably less science-based and more centered on short lead times, which may not be picked up by the industry dummies (Teirlinck & Spithoven, 2008). Furthermore, firms in Flanders and Wallonia seem to experience less influence of the R&D tax credit on the scale and speed of their R&D than firms located in Brussels.

Our second hypothesis stated that the behavioral additionality effects of R&D tax credits are stronger for firms that also receive an R&D subsidy versus firms that only benefit from tax credits. We test it by including, alongside the variable for tax credit importance, a dummy for firms that have also received subsidies. The multivariate probit results presented in Table 6 reveals that receiving the policy mix of tax credits and subsidies has positive and significant effects on all the outcomes we analyze. While the effect of the *tax importance* variable remains significant on the *Research vs Development* and *nr of projects* equations (which is consistent with the previous model), the effect of receiving subsidies is significant across all four specifications. However, Wald tests show that the positive moderating effect of subsidies on tax credits is significantly higher for the *nr of projects* than for *scale* and *speed* of R&D.

[Insert Table 6 here]

As argued in section 2, the underlying mechanism that results in the positive interaction between subsidies and tax credits may relate to the learning effects following the competition for R&D grants and – if successful – the direction they provide for additional investments, such as those made possible by tax credits. Even for financially less constrained firms that do not need subsidies to set up R&D projects, there may be a ‘disciplining role’ performed by the subsidy application process. While firms may have their own structured approach to initiate R&D projects, in order to obtain an R&D grant, firms need to write a proposal in which they think through the entire project, anticipate external reviewer comments, establish connections with potential R&D partners, etc. This is a learning experience for the firm, which it may not be able to reproduce entirely in internal processes and which creates a fertile basis for the use of tax credits. Once the firm is awarded an R&D grant, the resulting project may perform as a focal point to which additional R&D resources can be productively allocated.

We have also verified whether the relative importance of subsidies versus tax credits has an influence on the moderating effect of subsidies. However, conditional on receipt of a subsidy, we do not find that the precise proportions in the policy mix have an impact (see Table 7 in Appendix).

5. Conclusions

This paper addressed behavioral additionality effects of tax credits and considered these effects within a broader policy mix. Within the policy mix we investigated the influence of a treatment effect by means of R&D subsidies for companies benefitting from tax credits.

Our empirical evidence relates to a representative dataset of R&D active companies benefitting from R&D tax credits in Belgium in the period 2006-2010. These tax credits have been introduced in the year 2006 by means of a tax deduction on the wages of highly qualified researchers. Scale, speed, number of projects, and research orientation of the projects have been investigated based on a firm based survey measuring the effects by referring to the counterfactual situation that no tax credits would have been obtained. We combine propensity score matching with multivariate probit models to control for possible selection bias usually present in analyses regarding the effects of subsidy or tax credit frameworks. We are aware of the necessity of further research on behavioral additionality of the tax credit and on the topic of policy mix, especially on an international scale.

The first key contribution of our analysis is that it considers behavioral additionality effects of tax credits, complementing the literature on input and output additionality. We find that tax credits lead to behavioral additionality effects in specific dimensions of firm decision-making. In particular, tax credits cause firms not to ‘do more of the same’ (scale) nor ‘do the same thing faster’ (speed) but rather make more far-reaching changes to their R&D approach. Initiating additional projects and/or tipping the R&D-balance more towards research are decisions that firms arguably do not take overnight and may be expected to have a lasting impact on the firm’s R&D processes. Our finding that the effects on firm decision making increase with the importance of the tax credit for the firm can be seen as an argument in favor of a volume-based tax credit system in the sense that firms respond more strongly as the benefit increases. This attenuates concerns about the effectiveness of tax credits that have been raised in the literature, such as using them to fund R&D projects that yield the highest private return rather than the ones that should be promoted from a social point of view (Hall & Van Reenen, 2000), or opportunistic relabeling of expenses as research activities (Antonelli & Crespi, 2013).

Besides the role of the (importance of) tax credits as such, the other main insight in this paper is that R&D subsidies have a positive moderating effect on the behavioral additionality of tax credits. We do not find evidence for any additional effects of the precise proportion of subsidies and tax credits in the policy mix. A first implication of the ‘leverage’ of tax credits by subsidies is that a comprehensive R&D policy requires communication between the public authorities managing different mechanisms. Especially in the case of multi-level policy making, such as in our setting where federal and regional governments are responsible for different support measures, understanding the spillovers between instruments ensures overall policy coherence.

The finding of an interaction effect also raises questions with respect to ‘picking the winner’ strategies R&D funding agencies are (accused of) following. Whether this positive effect of subsidies on behavioral additionality of tax credits would hold if one expanded the set of subsidy beneficiaries is far from certain. Because of selection issues, firms that are currently not applying for subsidies may not use them as productively if they also received a grant. Indeed, prior research has shown that ‘picking the winner’ strategies are not necessarily a bad choice since they may result in a ‘virtuous Matthew effect’ (Antonelli & Crespi, 2013). Leaving aside the issue of the feasibility of exploiting the policy mix effect across a broader set of firms, a key takeaway from our results is that firms deal in thoughtful ways with available resources for R&D. However, while our results establish that subsidies affect the way tax credits are utilized, further qualitative research is called for to better understand the micro-foundations of the interaction effect. Avenues for future research include the construction of larger datasets in order to more accurately estimate additionality effects. This goal could be achieved by the introduction of additionality-related surveys in more OECD or EU countries, following the example of the Belgian Science Policy Office’s survey providing us with the data analysed in this paper. Finally, the consideration of longer time periods beyond the period of economic and financial turbulence that characterized our dataset would strengthen the generalizability of the results.

6. Tables

Table 1 Descriptive statistics, pre-matching

variable	tax credits only n=75	tax credits + R&D subsidies n=117	p-value
	Matching variables		
R&D intensity	26%	24%	0.72
ln(employees)	3.86	3.18	0.01
Tax leader	24%	38%	0.05
Current ratio	1.80	2.11	0.27
High-tech manuf.	21%	19%	0.67
High-tech serv.	27%	39%	0.09
Low-tech serv.	12%	9%	0.57
Low-tech manuf.	35%	31%	0.58
Brussels	8%	9%	0.89
Flanders	67%	63%	0.63
Wallonia	25%	28%	0.66
	Outcome variables		
Scale	51%	65%	0.05
Speed	43%	61%	0.01
R versus D	24%	52%	0.00
Projects	45%	62%	0.03

Table 2 Probit model for the use of tax credits and subsidies

	Coef.	Std. Err.
R&D intensity	-0.91**	0.38
ln(employees)	-0.20***	0.07
Tax leader	0.52**	0.22
Current ratio	0.04	0.07
High-tech manuf.	0.00	0.27
High-tech serv.	0.30	0.28
Low-tech serv,	-0.21	0.35
Flanders	0.14	0.37
Wallonia	0.07	0.39
Constant	0.78	0.51
N	192	
LR $chi^2(9)$	19.35	
Prob > chi^2	0.02	
Pseudo R^2	0.07	
Log likelihood	-118.77	

Table 3 Descriptive statistics of matched sample

variable	tax credit only	tax credit & R&D subsidies	p>T
R&D intensity	26%	25%	0.99
ln(employees)	3.86	3.24	0.69
Tax leader	24%	35%	0.89
Current ratio	1.80	1.93	0.82
High-tech manuf.	21%	20%	0.37
High-tech serv.	27%	34%	0.56
Low-tech serv.	12%	10%	0.67
Low-tech manuf.	35%	34%	0.67
Brussels	8%	8%	0.27
Flanders	67%	65%	0.57
Wallonia	25%	27%	1.00

Table 4 Average treatment effect on the treated

Variable	Treated	Controls	Difference	T-stat
Scale	63%	49%	14%	1.31
Speed	59%	36%	22%**	2.11
R vs D	53%	26%	27%**	2.77
Projects	60%	42%	18%	1.66

Table 5 Multivariate probit model testing H1

	scale		speed		R vs D		nr of projects	
	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.
Tax importance	**0.29**	**0.32**	**0.17**	**0.32**	**0.59***	**0.32**	**1.58*****	**0.36**
R&D intensity	0.31	0.41	0.28	0.37	0.21	0.39	0.78**	0.40
ln(employees)	-0.11	0.07	-0.05	0.07	-0.09	0.07	0.06	0.07
Tax leader	0.19	0.22	0.18	0.22	0.21	0.22	0.13	0.22
Current ratio	-0.03	0.07	0.06	0.08	-0.14	0.09	-0.02	0.08
High-tech manuf.	-0.24	0.29	-0.24	0.30	0.47*	0.28	0.40	0.30
High-tech serv.	-0.16	0.27	0.07	0.26	0.26	0.27	0.13	0.26
Low-tech serv.	-0.09	0.37	-0.26	0.38	0.14	0.36	0.48	0.37
Demand pull	-0.02	0.29	-0.53*	0.30	-0.51	0.32	-0.04	0.29
Tech. push	1.29***	0.47	1.40***	0.39	1.35**	0.59	0.51	0.48
Flanders	-1.22***	0.40	-0.87**	0.41	0.46	0.38	-0.28	0.35
Wallonia	-1.07***	0.41	-0.41	0.44	0.26	0.40	0.09	0.38
N	179							
Log pseudolikelihood	-346.29							
Wald test (χ^2)	107.6***							
LR test of all r=0 (χ^2)	181.66***							

Note: Wald tests show that the coefficient of *Tax importance* for the 'nr of projects'-equation is significantly different from the other equations.

Table 6 Multivariate probit model testing H2

	Scale		speed		R vs D		nr of projects	
	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.
Tax importance	**0.38**	**0.33**	**0.26**	**0.33**	**0.83****	**0.33**	**1.78*****	**0.37**
Subsidy dummy	**0.37***	**0.22**	**0.42****	**0.22**	**0.90*****	**0.22**	**0.62*****	**0.22**
R&D intensity	0.43	0.43	0.43	0.40	0.52	0.39	1.01**	0.41
ln(employees)	-0.09	0.08	-0.01	0.08	-0.03	0.08	0.12*	0.07
Tax leader	0.12	0.23	0.08	0.23	0.03	0.23	0.00	0.22
Current ratio	-0.03	0.08	0.05	0.08	-0.17*	0.09	-0.03	0.08
High-tech manuf.	-0.25	0.29	-0.25	0.30	0.46	0.30	0.39	0.31
High-tech serv.	-0.21	0.27	0.03	0.27	0.16	0.27	0.08	0.27
Low-tech serv.	-0.08	0.37	-0.23	0.36	0.26	0.37	0.57	0.38
Demand pull	0.01	0.29	-0.48	0.30	-0.41	0.35	0.05	0.30
Tech. push	1.33***	0.50	1.41***	0.39	1.32**	0.67	0.51	0.51
Flanders	-1.24***	0.42	-0.91**	0.40	0.38	0.40	-0.33	0.36
Wallonia	-1.07**	0.43	-0.44	0.43	0.20	0.42	0.08	0.39
N	179							
Log pseudolikelihood	-336.70							
Wald test (c²)	157.53***							
LR test of all r=0 (c²)	166.22***							

7. Appendix

Table 7 Multivariate probit model including dummies for importance of subsidies

	scale		speed		R vs D		nr of projects	
	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.	coeff.	std. err.
Tax importance	**0.40**	**0.35**	**0.36**	**0.36**	**0.92*** **	**0.35**	**1.78*** **	**0.40**
Subsidy dummy	**0.58** **	**0.29**	**0.58***	**0.30**	**1.11*** **	**0.31**	**0.56***	**0.31**
Subs. imp. 0-25%	**-0.19**	**0.43**	**-0.02**	**0.42**	**-0.19**	**0.44**	**0.26**	**0.48**
Subs. imp. 25-50%	**-0.16**	**0.35**	**-0.39**	**0.35**	**-0.06**	**0.36**	**-0.26**	**0.37**
Subs. imp. 50-75%	**-0.57**	**0.39**	**-0.35**	**0.39**	**0.00**	**0.42**	**0.17**	**0.41**
R&D intensity	0.69	0.46	0.46	0.43	0.59	0.43	0.88*	0.45
ln(employees)	-0.07	0.09	-0.03	0.08	0.03	0.09	0.09	0.09
Tax leader	0.01	0.24	0.00	0.24	-0.11	0.24	-0.04	0.23
Current ratio	-0.03	0.08	0.05	0.08	-0.19**	0.09	-0.01	0.08
High-tech manuf.	-0.21	0.32	-0.27	0.33	0.70**	0.33	0.36	0.34
High-tech serv.	-0.23	0.28	0.01	0.29	0.22	0.28	0.05	0.28
Low-tech serv.	-0.13	0.39	-0.27	0.39	0.32	0.39	0.59	0.39
Demand pull	-0.03	0.30	-0.51*	0.29	-0.48	0.37	-0.06	0.31
Tech. push	1.36***	0.53	1.39***	0.42	1.15*	0.68	0.68	0.57
Flanders	-1.22***	0.43	-0.89**	0.42	0.42	0.43	-0.30	0.37
Wallonia	-1.08**	0.45	-0.44	0.44	0.16	0.44	0.15	0.39
N	166							
Log pseudolikelihood	-306.93							
Wald test (c²)	258.52***							
LR test of all r=0 (c²)	150.02***							

Bibliography

Abadie, A., & Imbens, G. W. (2006). Large sample properties of matching estimators for average treatment effects. *Econometrica*, *74*(1), 235–267.

Aerts, K., & Schmidt, T. (2008). Two for the price of one?: Additionality effects of R&D subsidies: A comparison between Flanders and Germany. *Research Policy*, *37*(5), 806–822.

Almus, M., & Czarnitzki, D. (2003). The Effects of Public R&D Subsidies on Firms' Innovation Activities. *Journal of Business and Economic Statistics*, *21*(2), 226–236.

Antonelli, C., & Crespi, F. (2013). The" Matthew effect" in R&D public subsidies: The Italian evidence. *Technological Forecasting and Social Change*, *80*(8), 1523–1534.

Aranguren, M. J., de la Maza, X., Parrilli, M. D., Vendrell-Herrero, F., & Wilson, J. R. (2013). Nested Methodological Approaches for cluster policy evaluation: An application to the Basque country. *Regional Studies*, (ahead-of-print), 1–16.

Arqué-Castells, P. and P. Mohnen (2012). Sunk costs, extensive R&D subsidies and permanent inducement effects. *UNU-MERIT Working Paper Series 029, United Nations University*, Maastricht Economic and social Research and training centre on Innovation and Technology.

Arrow, K. (1962). Economic welfare and the allocation of resources for invention. In *The Rate and Direction of Inventive Activity* (R. Nelson., pp. 165–180). Princeton, NJ: Princeton University Press.

Bach, L. Matt, M. (2002). Rationale for science & technology policy. In Georghiou, L., Righby, J., Cameron, H. (Eds.), *Assessing the Socio-economic Impacts of the Framework Programme*. PREST. University of Manchester, Manchester.

Barge-Gil, A., & López, A. (2013). The complementarity effect of research and development on firm productivity. *Applied Economics Letters*, *20*(15), 1426–1430.

Bérubé, C., & Mohnen, P. (2009). Are firms that receive R&D subsidies more innovative? *Canadian Journal of Economics/Revue Canadienne D'économique*, *42*(1), 206–225.

Blanes, J. V., & Busom, I. (2004). Who participates in R&D subsidy programs?: The case of Spanish manufacturing firms. *Research Policy*, *33*(10), 1459–1476.

Bromiley, P. (1991). Testing a causal model of corporate risk taking and performance. *Academy of Management Journal*, *34*(1), 37–59.

Buisseret, T. J., Cameron, H. M., & Georghiou, L. (1995). What difference does it make Additionality in the public support of RD in large firms. *International Journal of Technology Management, 10*, *4*(5), 587–600.

Busom, I., Corchuelo Martínez-Azúa, B., & Martinez Ros, E. (2012). *Tax incentives or subsidies for R&D? UNU-MERIT Working Paper Series No. 056*. United Nations University, Maastricht Economic and social Research and training centre on Innovation and Technology.

Caiumi, A. (2010). The evaluation of the effectiveness of tax expenditures: A novel approach. *Institute for Studies and Economic Analysis (ISAE), Rome, Working Paper* 126.

Cappelen, A., Raknerud, A., & Rybalka, M. (2007). The effect of R&D tax credits on firm performance. Report 2007/22. *Statistics Norway: Oslo*.

Cappellari, L., & Jenkins, S. P. (2003). Multivariate probit regression using simulated maximum likelihood. *Stata Journal*, *3*(3), 278–294.

Clarysse, B., Wright, M., & Mustar, P. (2009). Behavioural additionality of R&D subsidies: A learning perspective. *Research Policy*, *38*(10), 1517–1533.

Corchuelo, B., & Martínez-Ros, E. (2009). The Effects of Fiscal Incentives for R&D in Spain. *Business Economic Series 02, Universidad Carlos III de Madrid*, *WP 09-23*.

Cunningham, P., Gök, A., & Larédo, P. (2012). The Impact of Direct Support to R&D and Innovation in Firms. *NESTA Working Paper No. 13/03.*

Cunningham, P., Edler, J., Flanagan, K., Laredo, P. (2013). Innovation policy mix and instrument interaction: a review. NESTA working paper No. 13/20.

Czarnitzki, D., Hanel, P., & Rosa, J. M. (2011). Evaluating the impact of R&D tax credits on innovation: A microeconometric study on Canadian firms. *Research Policy*, *40*(2), 217–229.

Czarnitzki, D., & Licht, G. (2005). Additionality of public R&D grants in a transition economy. *Economics of Transition*, *14*(1), 101–131.

Czarnitzki, Dirk, & Lopes-Bento, C. (2013). Value for money? New microeconometric evidence on public R&D grants in Flanders. *Research Policy*, *42*(1), 76–89.

David, P. A., Hall, B. H., & Toole, A. A. (2000). Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. *Research Policy*, *29*(4-5), 497–529.

Diez, M.-A. (2002). Evaluating New Regional Policies Reviewing the Theory and Practice. *Evaluation*, *8*(3), 285–305.

Dumont, M. (2012). Impact des subventions et des incitations fiscales sur la recherche et le développement des entreprises en Belgique (2001-2009). Report No. 8-12. Brussels, BE: Belgian Federal Planning Bureau.

Falk, R. (2007). Measuring the effects of public support schemes on firms' innovation activities: Survey evidence from Austria. *Research Policy*, *36*(5), 665–679.

Falk, R., Borrmann, J., Grieger, N., Neppl-Oswald, E., & Weixlbaumer, U. (2009). *Tax Incentive Schemes for R&D*. Report No. 4. Vienna, Austria: Austrian Institute for Economic Research.

Flanagan, K., Uyarra, E., Laranja, M. (2011). Reconceptualising the 'policy mix' for innovation. *Research Policy,* 40, 702–713.

Georghiou, L. (2002). Additionality and impact of R&D subsidies. *IWT-STUDIES*, *40*, 57–64.

Goolsbee, A. (1998). Does Government R&D Policy Mainly Benefit Scientists and Engineers? *The American Economic Review*, 88(2), 298-302.

Haegeland, T., & Møen, J. (2007). Input additionality in the Norwegian R&D tax credit scheme. *Statistics Norway Reports*, (47).

Hall, B., & Van Reenen, J. (2000). How effective are fiscal incentives for R&D? A review of the evidence. *Research Policy*, *29*(4–5), 449–469.

Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies*, *64*(4), 605–654.

Hyytinen, A., & Toivanen, O. (2005). Do financial constraints hold back innovation and growth?: Evidence on the role of public policy. *Research Policy*, *34*(9), 1385–1403.

Iacus, S. M., King, G., & Porro, G. (2011). Multivariate matching methods that are monotonic imbalance bounding. *Journal of the American Statistical Association*, *106*(493), 345–361.

Idea Consult and Clarysse, B. (2006). Study and Evaluation of the Behavioural Additionality of R&D Subsidies. Report for IWT, Brussels.

Kobayashi, Y. (2011). Effect of R&D Tax Credits for Small and Medium-sized Enterprises in Japan: Evidence from firm-level data. *Discussion papers 11066*, Research Institute of Economy, Trade and Industry.

Köhler, C., Laredo, P., & Rammer, C. (2012). The Impact and Effectiveness of Fiscal Incentives for R&D. NESTA Working Paper No. 12/01.

Latham, S. F., & Braun, M. R. (2010). Assessing the relationship between financial slack and company performance during an economic recession: an empirical study. *International Journal of Management*, *26*(1), 33.

Lechner, M. (1998). Training the East German Labour Force: Microeconometric Evaluations of Continuous Vocational Training After Unification. Springer. Heidelberg.

Lhuillery, S., Marino, M., Parrotta, P. (2013). Evaluation de l'impact des aides directes et indirectes à la R&D en France. *Rapport pour le Ministère de l'Ensegnement Supérieur et de la Recherche*, Paris, 2013.

Lokshin, B., & Mohnen, P. (2012). How effective are level-based R&D tax credits? Evidence from the Netherlands. *Applied Economics*, *44*(12), 1527–1538.

Luukkonen, T. (2000). Additionality of EU Framework Programmes, *Research Policy,* 29: 711-724.

Magro, E., & Wilson, J. R. (2013). Complex innovation policy systems: Towards an evaluation mix. *Research Policy*, *42*(9), 1647–1656.

Mathieu, A., van Pottelsberghe de la Potterie, B. (2010). A Note on the Drivers of R&D Intensity. *Research in World Economy*, *1*(1), 56.

Mullahy, J. (2011). Marginal Effects in Multivariate Probit and Kindred Discrete and Count Outcome Models, with Applications in Health Economics. Working Paper No. w17588. National Bureau of Economic Research.

Nauwelaers, C., Wintjes, R., 2003. Towards a new paradigm for innovation policies? In: Asheim, B., Isaksen, A., Nauwelaers, C., Totdling, F. (Eds.), Regional Innovation Policy for Small–Medium Enterprises. Edward Elgar, Cheltenham.

Nauwelaers, C., Boekholt, P., Mostert, B., Cunningham, P., Guy, K., Hofer, R.,Rammer, C., 2009. Policy Mixes for R&D Europe. E.C.-Directorate-General, UNU-Merit.

Nelson, R. R. (1959). The simple economics of basic scientific research. *The Journal of Political Economy*, *67*(3), 297–306.

Organisation for Economic Co-operation and Development. (2002). *Frascati Manual 2002: Proposed Standard Practice for Surveys on Research and Experimental Development*. Paris: OECD.

Organisation for Economic Co-operation and Development. (2006). *Government R&D Funding and Company Behaviour: Measuring Behavioural Additionality*. Paris: OECD.

Organisation for Economic Co-operation and Development. (2010). OECD Science, Technology and Industry Outlook 2010. OECD Publishing, Paris.

Organisation for Economic Co-operation and Development. (2013). Science, Technology and Innovation Outlook 2013. Paris, OECD.

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55.

Rubin, D. B. (1977). Assignment to Treatment Group on the Basis of a Covariate. *Journal of Educational and Behavioral Statistics*, *2*(1), 1–26.

Santamaría, L., Barge-Gil, A., & Modrego, A. (2010). Public selection and financing of R&D cooperative projects: credit versus subsidy funding. *Research Policy*, *39*(4), 549–563.

Takalo, T., Tanayama, T. and Toivanen, O. (2013). Estimating the benefits of targeted R&D subsidies. *The Review of Economics and Statistics*, 95(1): 255–272.

Takalo, T. and Tanayama, T. (2010). Adverse selection and financing of innovation: is there a need for R&D subsidies? *Journal of Technology Transfer,* 35, 16-41.

Teirlinck, P., & Spithoven, A. (2008). The Spatial Organization of Innovation: Open Innovation, External Knowledge Relations and Urban Structure. *Regional Studies*, *42*, 689–704.

Teirlinck, P., & Spithoven, A. (2012). Fostering industry-science cooperation through public funding: differences between universities and public research centres. *The Journal of Technology Transfer*, *37*(5), 676–695.

Teirlinck P., Dumont M. and Spithoven A., (2010). Corporate decision-making in R&D outsourcing and the impact on internal R&D employment intensity. *Industrial and Corporate Change*, 19, 6, 1867-1890.

Zúñiga-Vicente, J. Á., Alonso-Borrego, C., Forcadell, F. J., & Galán, J. I. (2014). Assessing the effect of public subsidies on firm R&D investment: a survey. *Journal of Economic Surveys*, *28*(1), 36–67.

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